EMPIRICAL ANALYSIS OF ROUGH SET CATEGORICAL CLUSTERING TECHNIQUES BASED ON ROUGH PURITY AND VALUE SET

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A thesis submitted in
fulfillment of the requirement for the award of the
Doctor of Philosophy in Information Technology

Faculty of Computer Science and Information Technology
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AUGUST 2017

I would like to dedicate my this PhD thesis to my beloved parents whose sincere prayers make it possible for me to be a successful computer and mathematics researcher. May Allah always bless them.

ACKNOWLEDGEMENT

Surely All praise is for Allah Almighty Who is the creator of this universe and Darood and Salam upon the Holy prophet Hazrat Muhammad (PBUH). Thanks to Allah Almighty Who enabled me to complete this research thesis with the continuous guidance and sincere cooperation of my kind supervisor Prof. Madya Dr Rozaida Binti Ghazali and my co-supervisor Prof. Dr. Mustafa Bin Mat Deris. In fact I learnt a lot from my worthy supervisors whose valuable suggestions, constructive comments, thought provoking ideas gave me this chance to make my research work a success with in a stipulated period. They are real role model and mentor for me.

I am also thankful to Allah Almighty Who bestowed upon me highly talented and sincere teachers, whose selfless guidance and tireless effort gave me opportunities and chances to complete this valuable research work. I extend my heartiest gratitude to my teachers especially the dean of faculty Prof. Madya Dr. Nazri Bin Mohd Nawi and Prof. Madya Dr Rathiah Binti Hashim for their sincere support, valuable comments and encouraging attitude. I am thankful to all my worthy teachers from the core of my heart they all remained cooperative honestly throughout my research work.

I will never forget the educational facilities and research oriented environment provided by the Faculty of Computer Science and Information Technology (FSKTM) and the Universiti Tun Hussien Onn Malaysia (UTHM). The sincere and continuous efforts of UTHM staff and administration to make available all modern and latest facilities to impart quality education in all fields are remarkable. It was their sincere efforts and approach that has made us able to learn information technology (IT) research and complete the research work under the guidance of able IT researchers, who are renowned in Malaysia and outside of the country in their field.

At last, it is a little sad to say that I could not get time for my old parents to serve them, but it is a fact that their prayers always remain with me and are still there with me throughout my education and research work. Their sincere prayers and advice helped me in every step of my life. Their prayers console me very much and I dedicate

this research work to them. I am really thankful to my sisters, brother, wife and kids whose best wishes and prayers always remain with me. I would also like to pay my best regard to my research fellow Rashid Naseem, my colleagues and all friends whose best wishes and prayers always remained with me throughout my research work. I would also like to thank Dr. Muhammad Imran who develop the uthmthesis LaTeX project for making the thesis writing process a lot easier for me.

ABSTRACT

Clustering a set of objects into homogeneous groups is a fundamental operation in data mining. Recently, attention has been put on categorical data clustering, where data objects are made up of non-numerical attributes. The implementation of several existing categorical clustering techniques is challenging as some are unable to handle uncertainty and others have stability issues. In the process of dealing with categorical data and handling uncertainty, the rough set theory has become well-established mechanism in a wide variety of applications including databases. The recent techniques such as Information-Theoretic Dependency Roughness (ITDR), Maximum Dependency Attribute (MDA) and Maximum Significance Attribute (MSA) outperformed their predecessor approaches like Bi-Clustering (BC), Total Roughness (TR), Min-Min Roughness (MMR), and standard-deviation roughness (SDR). This work explores the limitations and issues of ITDR, MDA and MSA techniques on data sets where these techniques fails to select or faces difficulty in selecting their best clustering attribute. Accordingly, two alternative techniques named Rough Purity Approach (RPA) and Maximum Value Attribute (MVA) are proposed. The novelty of both proposed approaches is that, the RPA presents a new uncertainty definition based on purity of rough relational data base whereas, the MVA unlike other rough set theory techniques uses the domain knowledge such as value set combined with number of clusters (NoC). To show the significance, mathematical and theoretical basis for proposed approaches, several propositions are illustrated. Moreover, the recent rough categorical techniques like MDA, MSA, ITDR and classical clustering technique like simple K-mean are used for comparison and the results are presented in tabular and graphical forms. For experiments, data sets from previously utilized research cases, a real supply base management (SBM) data set and UCI repository are utilized. The results reveal significant improvement by proposed techniques for categorical clustering in terms of purity (21%), entropy (9%), accuracy (16%), rough accuracy (11%), iterations (99%) and time (93%).

ABSTRAK

Pengelompokan satu set objek ke dalam kumpulan homogen adalah operasi asas dalam perlombongan data. Kebelakangan ini, perhatian banyak diberikan kepada pengelompokan data berasaskan kategori, iaitu objek data terdiri daripada atribut bukan berangka. Kebanyakan perlaksanaan teknik pengelompokan berasaskan kategori sedia ada adalah mencabar kerana sebahagiannya tidak dapat mengendalikan isu-isu ketidakpastian dan mempunyai masalah kestabilan. Dalam proses berurusan dengan data berasaskan kategori dan pengendalian ketidakpastian, teori set kasar telah menjadi mekanisme yang mantap dalam pelbagai aplikasi termasuk pangkalan data. Kategori set kasar berdasarkan teknik pengelompokan data seperti Teori-Informatik Bersandarkan Kekasaran (ITDR), Atribut Bersandarkan Maksimum (MDA) dan Atribut Signifikan Maksimum (MSA) telah mengatasi teknik-teknik terdahulu seperti Dwi-Kelompok (BC), Kekasaran Mutlak (TR) , Kekasaran Min-Min (MMR), dan Kekasaran Sisihan-Piawai (SDR). Kajian ini membentangkan kekangan dan isu-isu bagi teknik-teknik ITDR, MDA dan MSA ke atas set data tertentu di mana teknik-teknik ini gagal untuk memilih atau menghadapi kesukaran untuk memilih kelompok atribut yang terbaik. Selanjutnya, dua teknik alternatif yang dinamakan Pendekatan Ketulenan Kasar (RPA) dan Attribut Nilai Maksima (MVA) bagi mengkelompokkan data berasaskan kategori telah dicadangkan. Pembaharuan bagi kedua-dua teknik yang telah dicadangkan ini adalah berikut; mencadangkan definisi ketidakpastian baharu berdasarkan ketulenan bagi kekasaran pangkalan data hubungan, manakala MVA berbeza dengan teknik teori set kasar lain, yang mana teknik ini menggunakan pengetahuan domain seperti set nilai yang bergabung dengan beberapa kelompok (NoC) dalam memilih kelompok atribut yang terbaik. Bagi menunjukkan signifikasinya, asas matematik dan teori bagi pendekatan yang dicadangkan, beberapa cadangan telah digambarkan. Selain itu, teknik-teknik berasaskan kategori yang terkini seperti MDA, MSA, ITDR dan teknik pengelompokan klasik seperti K-mean asas digunakan sebagai perbandingan dan keputusan perbandingan dibentangkan di dalam

bentuk jadual dan grafik. Bagi kegunaan eksperimen, set data daripada kajian-kajian terdahulu digunakan seperti Supply Base Management (SBM) dan pangkalan data UC Irvine Machine Learning Repository (UCI). Keputusan menunjukkan prestasi bagi teknik yang dicadangkan adalah lebih baik dalam memilih atribut kelompok dan mengkelompokkan data berasaskan kategori dari segi ketulenan (21%), entropi (9%), lelaran (99%), masa (93%), ketepatan (16%), dan ketepatan kekasaran (11%).

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LIST OF SYMBOLS AND ABBREVIATIONS

RST	–	Rough Set Theory
MDA	–	Maximum Dependency Attribute
MSA	–	Maximum Significance Attribute
ITDR	–	Information Theory Dependency Roughness
RPA	–	Rough Purity Approach
MVA	–	Maximum Value Attribute
NoC	–	Number of Clusters
BC	–	Bi-Clustering
MMR	–	MinMin-Roughness
SDR	–	Standard Deviation Roughness
U	–	Universe of objects
SBM	–	Supply Base Management

LIST OF PUBLICATIONS

1. Jamal Uddin, Rozaida Ghazali, Mustafa Bin Mat Deris (2016), An Empirical Analysis of Rough Set Categorical Clustering Techniques , *PLoS ONE*, Accepted, DOI: 10.1371/journal.pone.0164803 (ISI Q1, IF=3.54)

2. Jamal Uddin, Rozaida Ghazali, Mustafa Bin Mat Deris, Rashid Naseem, Habib Shah (2016), A Survey on Bug Prioritization, *Artificial Intelligence Review, Springer*, PP 1-36, DOI: 10.1007/s10462-016-9478-6 (ISI Q2, IF=2.1)

3. Jamal Uddin, Rozaida Ghazali, Mustafa Bin Mat Deris, Tutut Herawan (2016), Does Number of Clusters Affects the Purity and Entropy of Clustering?, *International Conference on Soft Computing and Data Mining (SCDM)*, Vol 549, ISBN : 978-3-319-51279-2, Springer Conference.

CHAPTER 1

INTRODUCTION

1.1 Research background

In this present information age, it is believed that information prompts success and strength. The modern technologies like computers and satellites are collecting tremendous amounts of information for us. However, these huge amounts of data in disparate structures overwhelmed in recent years rapidly. Therefore, data base management system (DMBS) and organized data bases are developed (Zaïane, 1999). An efficient DMBS contributes towards effective retrieval of specific information from huge corpus of data. Dealing with huge collections of data, the needs such as automatic summarization of data, discovery of patterns in raw data and extraction of information helps in making better managerial choices. Different kinds of information are collected daily that includes scientific data, software engineering data, games, personal data, satellite sensing, digital media, text reports, business transactions, medical data, world wide web repositories, virtual worlds, surveillance video and pictures.

This enormous amount of data stored in databases, files and other repositories requires a powerful means for interpretation of such data, analysis and for the knowledge extraction that could help in decision-making. Knowledge discovery in databases (KDD) refer to the extraction of previously unknown but potentially useful information which is nontrivial and implicit from the data in databases (Zaïane, 1999). The data mining term being part of the knowledge discovery process is frequently used as synonyms for KDD. The KDD process includes steps like raw data collections leading to formation of new knowledge, data cleaning, data integration, data selection,

data transformation, data mining, pattern evaluation and knowledge representation. The data mining task that is employed determines the kind of information needed to be discovered. In general, there are two types of data mining tasks, that is descriptive and predictive tasks (Zaïane, 1999). Descriptive data mining tasks describe the general properties of the existing data, while the predictive data mining tasks attemps to make predictions based on inference on available data.

Many issues are still pending to be addressed like security, social, interface, mining methodologies, performance and data source before the data mining develops into a conventional and trusted discipline (Zaïane, 1999). The data mining functionalities include prediction, association analysis, classification, clustering, characterization and discrimination etc. The clustering is actually used to analyze accurately the data generated by different modern sources and has appeared as a powerful meta-learning tool. It is considered to be a concise model of the data in the absence of specific labeled information. In particular, the key objective of clustering is to categorize data into clusters so that similar objects are grouped in the same cluster according to specific metrics (Fahad *et al.*, 2014). The internal homogeneity and the external separation is considered by most researchers while describing a cluster (Xu & Wunsch, 2005; Norušis, 2011) i.e., similar objects in the same cluster while different objects in separate clusters.

The different clustering techniques can be broadly classified into partitioning, hierarchical, density, grid and model based approaches (Fahad *et al.*, 2014). Partitioning-based techniques specify the initial groups by reallocating them towards a union and all clusters are determined promptly. In hierarchy based clustering, depending on the medium of proximity the data is organized in a hierarchical manner. Similarly, density-based based approaches separates the data objects based on their regions of density, boundary and connectivity. Grid based technique divides the space of the data objects into grids. Whereas, in model based clustering techniques the fit between the given data and some (predefined) mathematical model is optimized (Fahad *et al.*, 2014). Many domains like academic result analysis of institutions, machine learning, image mining, medical dataset, software engineering, bioinformatics,

information retrieval and pattern recognition uses the core methodology of clustering (Wong *et al.*, 2000; Dharmarajan & Velmurugan, 2013; Naseem *et al.*, 2013; Britto *et al.*, 2014; Aggarwal & Reddy, 2014).

The particular choice of a clustering technique also relies tremendously on specific data type. The different data types are textual, discrete sequences, time series, uncertain data, categorical and multimedia data (Aggarwal & Reddy, 2014). There are several clustering techniques developed to combine objects of same characteristics, however the implementation of them is challenging due to certain issues like categorical data clustering, handling uncertainty, stability and efficiency issues. Different techniques for clustering data having only numerical values were proposed by Haimov *et al.* (1989); Wong *et al.* (2000); Shuanhu et al. (2004). Unlike numerical data, the multi-valued attributes known as categorical data have common values or common objects and association between both. To deal with categorical data, a number of clustering techniques have been developed (Huang, 1998; Guha, S.; Rastogi, 1999; Ganti & Ramakrishnan, 1999; Gibson & Kleinberg, 2000). Though, they contributed well to clustering process but they are not able to handle uncertainty (Herawan *et al.*, 2010a). In many cases where there is no sharp boundary between clusters, the uncertainty becomes an important real world issue.

Huang, Gupta and Kang (Huang, 1998; Kim *et al.*, 2004) explored fuzzy sets to handle uncertainty in categorical data clustering. However, to attain the stability and to control the membership fuzziness these techniques require multiple runs (Herawan *et al.*, 2010a). Zdzislaw Pawlak introduced rough set theory (RST) (Pawlak, 1991; Pawlak et al., 1995), a mathematical tool to deal with vagueness and uncertainty. Many researchers and practitioners are attracted towards RST by contributing essentially to the applications and development in the fields of artificial intelligence, decision support systems, machine learning, knowledge acquisition, decision analysis, pattern recognition, expert systems, cognitive sciences, inductive reasoning, and knowledge discovery from data bases (Pawlak & Skowron, 2007). Many interesting applications, the basic ideas of RST and its extensions can be found in several books, issues of the transactions on rough sets, special issues of other journals, international conferences,

proceedings and tutorials (Pawlak & Skowron, 2007).

The RST is a viable system to deal with uncertainty in clustering process of categorical data. RST was originally a symbolic data analysis tool now being developed for cluster analysis (Düntsch & Gediga, 2015). In rough categorical clustering, mainly the data set is expressed as the decision table by introducing a decision attribute. Most of these methods assume one or more given partitions of the data set aiming to find a cluster which best represents the data according to some predefined measure. Set approximation and reduct based methods are the two main ideas of the rough set model which are promising for applications. Tolerance rough set clustering (Ngo & Nguyen, 2004) and rough-K-Means clustering (Peters, 2006) are the examples of set approximation methods. Despite of having satisfactory results, these methods have issues as they depend on several parameters and thresholds (Düntsch & Gediga, 2015). The reduct based methods either work as pre-processing tool or as a tool for cluster generation but the problem of time complexity has not been solved yet (Düntsch & Gediga, 2015).

In RST, a subset of universe can be represented in terms of equivalence classes as clustering of universe. Therefore, RST has been successfully applied for selecting best suitable clustering attribute. The pioneer techniques to select clustering attribute are developed by Mazlack *et al.* (2000) which includes Total Roughness (TR) and Bi-Clustering (BC) . These techniques work on the accuracy of roughness (approximation accuracy average) in the RST. Later on, another rough categorical clustering approach named Min-Min Roughness (MMR) was proposed by Parmar *et al.* to improve previous techniques (Parmar *et al.*, 2007). Despite of MMR's better performance, issues like accuracy, computational complexity and purity are yet to be addressed.

In 2010, a technique based on the dependency of attributes was introduced by Herawan *et al.* (2010a) named maximum dependency of attributes (MDA) which uses rough set information system for categorical data clustering. Hassanein and Elmelegy in 2013, proposed maximum significance of attributes (MSA) that utilized the RST concept of significance of attributes for selecting clustering attribute (Hassanein & Elmelegy, 2013). Recently, Park and Choi introduced information-theoretic

dependency roughness (ITDR) technique (Park & Choi, 2015b) which finds the entropy roughness to choose the suitable clustering attribute. It is another rough clustering technique that uses the information-theoretic dependencies of categorical attributes in information systems.

1.2 Research Motivation

Today the world is full of data and every day people encounter a large amount of information and they store or represent it as data for further analysis and management. One of the vital means in dealing with these data is to classify or group them into a set of categories or clusters. Rough Set Theory (RST) is a powerful mathematical tool proposed by Pawlak (Pawlak & Skowron, 2007) successfully applied to deal with vagueness and uncertainty in data analysis. The concept of rough set theory in this research work is utilized in terms of data in an information system.

Rough set theory has the ability of decision making in the presence of uncertainty and vagueness. Moreover, it can represent a subset of universe in terms of equivalence classes of partition of the universe. Obviously, every subset of attributes induces unique indiscernibility relation which is an equivalence relation and hence, induces unique clustering. This notion of indiscernibility is very attractive, since each indiscernible relation is also a sort of cluster. In this study, the indiscernibility is used as a measure of similarity without any distance function for clustering the objects.

Recently, the problem of clustering categorical data has received much attention in many fields from statistics to psychology. The categorical data unlike numerical data cannot be naturally ordered. Therefore, those clustering techniques dealing with numerical data cannot be used to cluster categorical data. In addition, very less work has been done for clustering the categorical data. A well-known approach for clustering categorical data is using rough set theory (Park & Choi, 2015a). Originally the motivation and inspiration for this study came from exploring useful limitations and issues of existing rough categorical clustering techniques (Mazlack *et al.*, 2000; Parmar *et al.*, 2007; Herawan *et al.*, 2010a; Hassanein & Elmelegy, 2013; Park & Choi,

2015b). This research is conducted in order to come with more general, efficient and better rough categorical clustering techniques. The MDA, MSA and ITDR techniques outperformed their previous techniques such as BC, TR, MMR etc, however, they have certain issues like accuracy, purity, generalizability and computational complexity. On several data sets, these techniques fail or face difficulties in choosing the suitable clustering attribute. Some of the limitations are outlined:

1. MDA technique cannot perform well on data sets with attributes having zero or equal dependency value.
2. MSA technique also fails to select clustering attribute on data sets having attributes with zero or equal significance value.
3. ITDR techniques face issues like random attribute selection and integrity of classes due to presence of entropy measure.

Accordingly in this work, two rough set based categorical clustering techniques are proposed. The first one, information theoretic Rough Purity Approach (RPA) is introduced by establishing a new rough set metric of uncertainty which is rough purity for categorical data clustering. The proposed RPA technique relates the concept of information theoretic purity to rough sets. Considering the domain knowledge of the data set, the second technique Maximum Value Attribute (MVA) is proposed. Here, the rough value set of an attribute is combined with number of clusters. This technique chooses the suitable clustering attribute on basis of maximum number of clusters by an attribute. Several propositions and experiments on benchmark data sets demonstrate the significance, novelty and contribution of these proposed techniques to practical systems.

1.3 Research Objectives

The research objectives are listed as follows:

1. To propose a new rough set based categorical clustering technique Rough Purity Approach that takes into account the purity of attributes.
2. To propose another rough set based categorical clustering technique Maximum

Value Attribute that takes into account the value set of attributes combined with number of clusters.

3. To elaborate the performance of proposed techniques on real and benchmark datasets by comparing them with the recent baseline rough categorical clustering techniques like Maximum Dependency Attribute, Maximum Significant Attribute and Information Theoretic Dependency Roughness and classical K-mean clustering algorithm using accuracy, purity, rough accuracy, time and iterative complexity (Big O notation) and entropy.

1.4 Research Scope

This research only focuses on proposing two rough set theory based categorical clustering techniques named RPA and MVA. The proposed and existing MDA, MSA, ITDR and classical K-mean techniques are analyzed on several benchmark (UCI and KEEL repositories) and a real Supply Base Management (SBM) data set. The experimental results are evaluated using metrics like accuracy, purity, rough accuracy, number of iterations, respond time and entropy.

1.5 Research Significance

The system implementation is significant by two ways in this research. Firstly, information-theoretic purity is introduced as a new definition to measure the uncertainty using RST for categorical data clustering. Secondly, a domain knowledge about data like rough value set is utilized to develop another rough categorical clustering technique combined with internal evaluation measure like number of clusters. Both these approaches show significant improvement for clustering categorical data not only in terms of time and iterations but also in terms of accuracy, purity, entropy and rough accuracy.

1.6 Thesis Organization

The remaining thesis is arranged as below:

Chapter 2 discusses some fundamental concepts and overview of existing work on clustering the categorical data using RST. It comprises of an information system notion in rough relational database, an indiscernibility relation, set approximations and quality of approximations. This chapter discusses the literature review of existing work for cluster analysis, cluster validation, SBM, RST and rough categorical data clustering. Moreover, it also presents the analysis and limitations of some existing rough categorical data clustering techniques with the help of examples.

Chapter 3 discusses the proposed techniques of clustering the categorical data, named Rough Purity Approach (RPA) and Maximum Value Attribute (MVA). The notion of purity using rough set theory and the value set cardinality are presented. Moreover, the evaluation metrics used in this research are also defined. Several propositions and examples are illustrated to show the significance of proposed techniques.

Chapter 4 illustrates the results of experiments on proposed techniques. An empirical study on ten small, fifteen benchmark data sets and a real SBM data set demonstrates the better performance of proposed techniques. Moreover, they are compared with most recent and leading rough set-based categorical clustering techniques. All the experimental results are discussed and analyzed in detail by presenting them in form of tables and graphs.

Finally, Chapter 5 gives concluding remarks, accomplished objectives, contributions and future work.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

The previous chapter demonstrated that cluster analysis and rough set clustering techniques are widely utilized for numerical and categorical data in various forms. Accordingly, this chapter gives an overview of related work on cluster analysis, validation criteria, rough set theory and rough categorical data clustering.

This chapter comprises of nine sections. An overview of cluster analysis techniques and existing work on them are discussed in Section 2.2. The existing work in the field of supply base management is summarized in Section 2.3. The detail of cluster evaluation measures are described in Section 2.4. Similarly, Section 2.5 explains some preliminaries and related research work on rough set theory. Section 2.6 illustrates the overview of existing research on categorical data clustering. Section 2.7 presents the analysis of best recent rough categorical clustering techniques to explore their limitations. Section 2.8 discusses the scenario that leads to research framework. Section 2.9 summarizes the chapter.

2.2 Cluster analysis

Clustering is one of the most important unsupervised learning tasks in which the objects are divided into clusters so that similar objects are combined in the same cluster while dissimilar objects in separate clusters. Clustering is widely used in many fields, such as text mining (Naresh Kumar Nagwani, 2012), image analysis (Li

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